



Similar risk of kidney failure among patients with blinding diseases who receive ranibizumab, aflibercept, and bevacizumab: an OHDSI Network Study

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6/25/2024



## SOS Challenge Weekly Tutorial Schedule 2023

Date	Times	Торіс
Mar. 28	11 am / 7 pm ET	SOS Week 1 Tutorial: Initiating A Network Study
Apr. 4	11 am / 7 pm ET	SOS Week 2 Tutorial: Data Diagnostics
Apr. 11	11 am / 7 pm ET	SOS Week 3 Tutorial: Phenotype Development
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May 16	11 am / 7 pm ET	SOS Week 8 Tutorial: Evidence Synthesis
May 23	11 am / 7 pm ET	SOS Week 9 Tutorial: Interpreting The Results





# Background: anti-VEGF medications

- Systemic administration of anti-VEGF agents have known adverse kidney side effects
  - Acute kidney injury
  - Proteinuria
  - Hypertension
  - Vascular clotting events
  - Glomerular disease
  - Risk factors for: kidney failure (need for renal replacement therapy with dialysis or kidney transplant, aka end stage kidney disease or end stage renal disease)

Hanna RM, Barsoum M, Arman F, Selamet U, Hasnain H, Kurtz I. Nephrotoxicity Induced by Intravitreal Vascular Endothelial Growth Factor (VEGF) inhibitors: Emerging Evidence. *Kidney Int*. 2019;96(3):572-580. doi:10.1016/j.kint.2019.02.042 Gurevich F, Perazella MA. Renal Effects of Anti-angiogenesis Therapy: Update for the Internist. *Am J Medicine*. 2009;122(4):322-328. doi:10.1016/j.amjmed.2008.11.025 Izzedine H, Escudier B, Lhomme C, et al. Kidney Diseases Associated With Anti-Vascular Endothelial Growth Factor (VEGF). *Medicine*. 2014;93(24):333-339. doi:10.1097/md.000000000000207 Brandes, A. A., Bartolotti, M., Tosoni, A., Poggi, R. & Franceschi, E. Practical Management of Bevacizumab-Related Toxicities in Glioblastoma. *Oncol* **20**, 166–175 (2015).

## Intravitreal Anti-VEGF and Systemic Absorption



Drug	Size	Systemic Elimination (half-life)
Ranibizumab	48 kDa	2 hours
Aflibercept	115 kDa	5-6 days
Bevacizumab	149 kDa	20 days

Detectable/elevated serum drug levels Decreased plasma concentrations of free-VEGF

## Bevacizumab > aflibercept >> ranibizumab

**Question**: Is there evidence for preferentially choosing ranibizumab to lower the risk of kidney failure?

https://www.randeye.com/intravitreal-injection/

Avery RL, Castellarin AA, Steinle NC, et al. SYSTEMIC PHARMACOKINETICS AND PHARMACODYNAMICS OF INTRAVITREAL AFLIBERCEPT, BEVACIZUMAB, AND RANIBIZUMAB. Retin. 2017;37(10):1847-1858. doi:10.1097/iae.00000000001493 https://www.accessdata.fda.gov/drugsatfda\_docs/label/2009/125085s0169lbl.pdf

# <u>Pilot Study (OHDSI SOS Challenge):</u> Intravitreal anti-VEGF and Kidney Failure

 Is the risk of kidney failure associated with intravitreal anti-VEGF exposure in patients with blinding diseases (DR/DME, AMD, VO) different among patients who receive ranibizumab, aflibercept, and bevacizumab?

**<u>Hypothesis</u>**: in pairwise comparisons, lower risk of kidney failure in patients with blinding diseases who are exposed to ranibizumab, as compared to aflibercept or bevacizumab

## **OHDSI** Tools: Atlas



## Target cohort definition: bevacizumab



New users of anti-VEGF (3 monthly loading doses) DR/DME, AMD, VO ≥1 year observation prior observation

Exclude systemic malignancies

Atlas: publicly available, web-based tool

# OHDSI Tools: Strategus pipeline, HADES packages

🗊 Packages

### Analysis #1:

 Incidence rate of kidney failure while on treatment with anti-VEGF

#### Population-level estimation

#### Patient-level prediction

Characterization

Cohort construction and evaluation

Evidence Quality

Supporting packages

### Packages

Learn more..

🌮 Publications

🕑 Validation

🕲 Support 👻

Below are the packages included in HADES. For each package a link is provided with more information, including instructions on how to install and use the package.

🔑 Developers 👻

📕 Study packages 👻

### Population-level estimation

🕤 CohortMethod	SelfControlledCaseSeries	SelfControlledCohort
New-user cohort studies using large- scale regression for propensity and outcome models. Learn more	Self-Controlled Case Series analysis using few or many predictors, includes splines for age and seasonality. Learn more	A self-controlled cohort design, where time preceding exposure is used as control. Learn more
TevidenceSynthesis		
Routines for combining causal effect		
estimates and study diagnostics		
across multiple data sites in a		
distributed study.		

### Patient-level prediction

TetientLevelPrediction	C DeepPatientLevelPrediction	TensemblePatientLevelPrediction
Build and evaluate predictive	Performing patient level prediction	Building and validating ensemble
models for user-specified outcomes,	using deep learning	patient-level predictive models.
using a wide array of machine	Learn more	Learn more
learning algorithms.		
Learn more		
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### Characterization Various types of characterizations of a target and outcome cohort. Learn more...

#### Characterization

# OHDSI Tools: Strategus pipeline, HADES packages

Packages

### Analysis #2:

- Large-scale propensity score method to match patients in each comparison group using 1:1 propensity score matching
- Cox proportional hazards models to estimate risk of kidney failure while on treatment
- Random effects meta-analysis was performed to combine per site hazard ratio estimates into a single network-wide estimate

Population-level estimation					
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	opu	lation-	ievei	esumation	

#### Patient-level prediction Characterization

- Cohort construction and evaluation
- Evidence Quality
- Supporting packages

### Packages

Publications

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# Anti-VEGF OHDSI Study: Process



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## Collectively: 485 million patients

### Administrative Claims Databases

IBM Health MarketScan Medicare Supplemental and Coordination of Benefits Database (MDCR)

IBM Health MarketScan Commercial Claims and Encounters Database (CCAE)

IBM Health MarketScan Multi-State Medicaid Database (MDCD)

Optum's de-identified Clinformatics<sup>®</sup> Data Mart Database - Socio-economic Status (SES)

Japan Medical Data Center (JMDC)

IQVIA PharMetrics<sup>®</sup> Plus for Academics Database (NEU)

### **Electronic Health Record Databases**

Optum<sup>®</sup> de-identified Electronic Health Record data set (Optum EHR)

Johns Hopkins Medical Enterprise (JHME)

Department of Veterans Affairs (VA)

Columbia University Medical Center (CUMC)

Stanford University (STARR)

University of Southern California (USC)

# Anti-VEGF OHDSI Study: Results

- 6.1 million patients with blinding diseases (DR/DME, AMD, VO)
  - 240,247 new users of monthly anti-VEGF
    - 37,189 received ranibizumab
    - 39,447 aflibercept
    - 163,611 bevacizumab
  - 1209 kidney failure outcomes
- Age-sex standardized incidence proportion of kidney failure: **680 per 100,000** persons
  - [US Renal Data System: age-sex standardized incidence proportion of 36.3 per 100,000 persons in
    2020]

## Anti-VEGF OHDSI Study: Results



## Conclusions

- No difference in the risk of kidney failure among patients who receive ranibizumab, aflibercept, bevacizumab
- Ophthalmologists are free to choose between intravitreal anti-VEGF agents

## Conclusions

- Speed and scale of observational health research when there is a CDM, well-established distributed data network, open-source tooling
  - Analysis in 9 weeks
  - Project initiation to publication I year
- Great value and potential for distributed data network studies in ophthalmology









## Similar Risk of Kidney Failure among Patients with Blinding Diseases Who Receive Ranibizumab, Aflibercept, and Bevacizumab

An Observational Health Data Sciences and Informatics Network Study

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